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Research article

# Are per capita carbon emissions predictable across countries?

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ABSTRACT

*Background:* China and other developing countries in Asia follow similar economic growth patterns described by the flying geese (FG) model, which explains the "catching-up" process of industrialization in latecomer economies. Japan, newly industrialized economies, and China have followed this path, with similar economic development trajectories. Based on the FG model, we postulated a "flying S" hypothesis stating that if a country is located within an FG region and its energy matrix is relatively constant, its per capita $CO_2$ emission curve will mirror that of "leading geese" countries in the same FG group.
*Method:* Historical $CO_2$ emissions data were obtained from literature review and national reports and were calculated using bottom-up methods. A sigmoid-shaped, non-linear mixed effect model was applied to examine ex post data with 1000 simulated predictions to construct 95% empirical bands from these fits. By multiplying by estimated population, we predicted total emissions of selected FG countries.
*Results:* Per capita $CO_2$ emissions from the same FG group mirror each other, especially among second and third industrial sectors. We estimated an annual 18,252.24 million tons of $CO_2$ emissions ($MtCO_2$) (95% CI = 9458.88–23,972.88) in China and 8281.76 MtCO2 (95% CI = 2765.68–14,959.12) in India in 2030.
*Conclusion:* This study bridges the macroeconomic FG paradigm to study climate change and proposes a "flying S" hypothesis to predict greenhouse gas emissions in East Asia. By applying our theory to empirical data, we provide an alternative framework to predict $CO_2$ emissions in 2030 and beyond.

## 1. Introduction

The flying geese model (FG) of economic development describes industrial migration and economic development patterns in East Asia (Kojima, 2000). Like the first goose in a V-shaped formation, one economy can lead others toward industrialization, passing down low value-added and labor-intensive industries as its own incomes rise and it moves into higher value-added industries (Kojima, 2000). Japan, East Asian newly industrialized economies (NIEs; including Korea, Taiwan, Hong Kong, and Singapore), and some countries in the Association of Southeast Asian Nations (ASEAN) followed this industrial ladder to achieve economic success in the late 20th century (Kasahara, 2013). Further, this pattern of economic growth and industrial transition still holds strongly in China (Kwan, 2002; Venkatachalam Anbumozhi, 2017).

Logistic curves (i.e., S-shaped sigmoid curves) can describe the evolution of economic growth (Kwasnicki, 2013) coincident with Rostow's stages. Walt Whitman Rostow's major macroeconomic growth model consists of five basic stages (Kojima, 2000): traditional society (Kasahara, 2013), preconditions for take-off (Kwan, 2002), take-off (Venkatachalam Anbumozhi, 2017), drive to maturity, and (Kwasnicki, 2013) age of high mass consumption (Rostow, 1960). Rostow asserted that "countries go through each of these stages fairly linearly, and set out a number of conditions that were likely to occur in investment, consumption, and social trends at each state."

While economic growth is the leading driving force, other factors, including population, industrialization and advanced technology, would affect energy consumption. Economic growth patterns in East Asia are similar within the region but are unique compared to economies in Western, Latin American (Nancy Birdsall, 1997), or African countries (Ishikawa, 2007). Except for Japan, most countries in East Asia went through industrialization after World War II (Kohli, 1994; Hunter and Shumpeter, 2000). Mirroring Rostow's theory of five stages, most East Asian countries in the FG group first produce labor-intensive

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consumer goods, such as textiles. When energy-intensive industries, such as concrete and steel industries, start booming, earlier industries lose competitive advantage due to a rise in wages (Hsu and theory, 2016). Energy-intensive industries then are subsequently replaced by capital-intensive industries, such as finance, service, and high technology (Kojima, 2000). Although scales might vary widely, FG countries consistently follow these stages (Kwan, 2002). In fact, both theories could be regarded as two sides of the same coin in the context of explaining economic growth patterns in East Asia (Hsu and theory, 2016), by providing microeconomic understanding to macroeconomic phenomenon.

Concomitant with economic development are rising carbon dioxide ($CO_2$) emissions. Per capita $CO_2$ emission in a country is proportional to its per capita energy consumption, given the energy matrix is constant across time. Further, considering constant energy matrix, the same logic in similarity of industrial migration patterns can apply to similar patterns of per capita $CO_2$ emissions among countries in the same FG group.

Therefore, we hypothesized that per capita $CO_2$ emission trajectory in one country can forecast per capita $CO_2$ emission in another under two assumptions (Kojima, 2000): the countries fit into the same FG group, and (Kasahara, 2013) both predictor and predicted countries have relatively constant energy matrices across time. The theory would apply even with substantial differences in industrial compositions and policies between countries, as long as the life cycle of most industries follow patterns described in FG theory. We call this pattern "flying S" and used it to predict emissions in East Asian countries.

## 2. Methods

### 2.1. Study period and data extraction

All data were obtained from World Bank (The World Bank. World Ban, 2017), except data for Taiwan and China. Emission data in Taiwan is not available from World Bank, and Chinese emission data from World Bank might be overestimated by up to 14% (2.49 gigatonnes of carbon) (Liu et al., 2015). Therefore, data for Taiwan and China were obtained from supplementary sources and calculated separately. Historical emission data were collected from the China Energy Statistical Yearbook (Department of Energy Statistics National Bureau of Statistics PsRoC, 2016) for China (1980–2015) and the Bureau of Energy, Ministry of Economic Affairs (Bureau of Energy Ministry, 2017) for Taiwan (1961–2015). All unit conversions and step-by-step calculations are summarized in Appendix 1. In short, we followed the 2006 Intergovernmental Panel on Climate Change (IPCC) guidelines for national greenhouse gas (GHG) inventory using a bottom-up method, where $i$ denoted different types of fossil fuels:

$$\begin{aligned} CO_2\ \text{emission} &= [\text{Emission from electricity \& heat}] \\ &\quad + \left[\sum_i \text{Fuel consumption}_i \times \text{Emission factor}_i \right. \\ &\quad \left. \times\ \text{Oxidation factor}_i \right] \end{aligned}$$

Oxidation factor was set to 1 by default; for Taiwan, emission factors were IPCC default values. Because applying IPCC default values for emission factors might lead to substantial errors in China, we carefully selected the most suitable factors for China from different sources, which are summarized in Appendix 1.

Nominal GDP and chain-weighted GDP were obtained and calculated at 2011 deflated values in China (National Bureau of Statistics of the People's Republic of China, 2017; National Statistics Taiwan, 2017) and Taiwan (National Bureau of Statistics of the People's Republic of China, 2017; National Statistics Taiwan, 2017). By-sector emission data and GDP were only available from the National Bureau of Statistics in China (National Bureau of Statistics of the People's Republic of China, 2017) and Statistical Bureau in Taiwan (National Statistics Taiwan, 2017). Sectoral classifications differed and therefore were summarized into four comparable categories of primary (farming), secondary (industry), tertiary (trade and transport), and residential consumption (Appendix 2).

### 2.2. Assumptions check

Literature review indicated that 12 countries/economies in East Asia were well known in the same FG group (Kasahara, 2013). To check the constant energy matrix assumption, percentages of total primary energy supply (TPES) of major brown energy sources (coal, gas, and oil) were calculated from 1991 to 2015 (International Energy Agen, 2018).

### 2.3. Analytic model

We applied non-linear mixed effect modeling to examine ex post data and predict per capita emissions for selected countries. Our model was as follows:

$$(\text{Per capita } CO_2 \text{ emission})_{it} = \frac{P_0 + P_1 \times (\text{Coal consumption})_i}{1 + e^{-\left(\frac{t - \text{year}_i}{s}\right)}} + \varepsilon_{it}$$

The formula is a modified sigmoid curve for country $i$ in year $t$. $P_0 + P_1 \times (\text{Coal consumption})_i$ is the country-specific plateau for per capita $CO_2$ consumption, which was regressed on average coal consumption percentage for country $i$ (over years in which data was available). The scale factor $s$, addressing the "catching up" process, was assumed fixed and estimated as 11.32 years from the regression model. $\text{Year}_i$ denotes country-specific transition years when growth rate begins slowing down (i.e., inflection point in the sigmoid curve).

Due to the difficulty in obtaining confidence bands in non-linear mixed effects least squares, we simulated 1000 predictions from the model fit and constructed 95% pointwise confidence bands from these fits. Specifically, the initial model fit provided estimates $(\hat{P}_0, \hat{P}_1, \widehat{\text{year}}_i, \hat{s})$ with respective covariance matrix, $\hat{\Sigma}$. We sampled replicates $\left(\hat{P}_0^{(b)}, \hat{P}_1^{(b)}, \widehat{\text{year}}_i^{(b)}, \hat{s}^{(b)}\right)$, for $b = 1, \cdots, 1000$, from a multivariate normal distribution with mean $(\hat{P}_0, \hat{P}_1, \widehat{\text{year}}_i, \hat{s})$ and covariance $\hat{\Sigma}$, which in turn were used to predict $(\text{Per capita } CO_2 \text{ emission})_{it}^{(b)}$ for each $i$ and $t$, using the modified sigmoid model. We constructed bands by taking the 2.5th and 97.5th percentile observations $(\text{Per capita } CO_2 \text{ emission})_{it}^{(b)}$ over replicates $b = 1, \cdots, 1000$ for each $i$ and $t$. We further multiplied the estimated population (Wulf, 2018) by per capita $CO_2$ emissions to obtain total emissions from one country. All analyses were performed in R 3.2.

To validate our model, we fitted our sigmoid curve to the subset before and including the year 2010. We predicted on the years 2006–2010 as part of the internal validation, and predicted on the years after 2010 as part of the external validation. Our validation metric is the residual sum of squares (RSS), computed for both the internal and external portions:

$$\begin{aligned} \text{RSS}_{\text{internal}} &= \sum_{t=2006}^{2010} \sum_{i=1}^{6} (\varepsilon_{it})^2 \\ &= \sum \left(\text{Per capita} CO_2 \text{emission}_{it} - \widehat{\text{Per capita} CO_2 \text{ emission}_{it}}\right)^2 \end{aligned}$$

$$\begin{aligned} \text{RSS}_{\text{external}} &= \sum_{t=2011}^{2015} \sum_{i=1}^{6} (\varepsilon_{it})^2 \\ &= \sum \left(\text{Per capita} CO_2 \text{emission}_{it} - \widehat{\text{Per capita} CO_2 \text{ emission}_{it}}\right)^2 \end{aligned}$$

$\widehat{\text{Per capita } CO_2 \text{ emission}_{it}}$ = Prediction based off fit on data ≤ year 2010.

**Table 1**
Mean, standard deviation (SD), and mean-to-SD ratio of production and import of major brown energy sources in East Asian countries, 1991–2015.[a]

| Country | Total primary energy supply | Mean | SD | Ratio |
|---|---|---|---|---|
| China | Coal | 64.47% | 4.75% | 13.58 |
| | Gas | 2.59% | 1.27% | 2.05 |
| | Oil | 17.11% | 1.57% | 10.90 |
| HK | Coal | 48.55% | 11.12% | 4.36 |
| | Gas | 14.08% | 7.64% | 1.84 |
| | Oil | 32.69% | 9.54% | 3.43 |
| India | Coal | 36.34% | 4.37% | 8.31 |
| | Gas | 5.51% | 1.08% | 5.10 |
| | Oil | 23.41% | 1.74% | 13.46 |
| Indonesia | Coal | 10.12% | 4.65% | 2.18 |
| | Gas | 17.71% | 1.40% | 12.62 |
| | Oil | 35.01% | 1.43% | 24.57 |
| Japan | Coal | 20.71% | 3.45% | 6.00 |
| | Gas | 15.15% | 4.60% | 3.29 |
| | Oil | 48.37% | 4.63% | 10.44 |
| Korea | Coal | 24.28% | 4.17% | 5.82 |
| | Gas | 10.85% | 4.45% | 2.44 |
| | Oil | 48.59% | 10.00% | 4.86 |
| Malaysia | Coal | 10.03% | 6.11% | 1.64 |
| | Gas | 42.93% | 5.17% | 8.31 |
| | Oil | 42.32% | 7.36% | 5.75 |
| Philippines | Coal | 13.63% | 6.22% | 2.19 |
| | Gas | 3.77% | 3.51% | 1.07 |
| | Oil | 38.64% | 6.26% | 6.18 |
| Singapore | Coal | 0.20% | 0.44% | 0.44 |
| | Gas | 17.67% | 12.17% | 1.45 |
| | Oil | 80.40% | 12.98% | 6.19 |
| Taiwan | Coal | 34.12% | 4.38% | 7.80 |
| | Gas | 8.27% | 2.89% | 2.86 |
| | Oil | 44.36% | 4.92% | 9.01 |
| Thailand | Coal | 11.86% | 1.34% | 8.87 |
| | Gas | 22.99% | 5.65% | 4.07 |
| | Oil | 43.58% | 4.01% | 10.86 |
| Vietnam | Coal | 19.55% | 6.24% | 3.14 |
| | Gas | 7.41% | 5.54% | 1.34 |
| | Oil | 25.66% | 4.26% | 6.03 |

[a] Data are from the International Energy Agency (International Energy Agen, 2018).

## 3. Results

We examined empirical data from World Bank and, for Taiwan and China, from supplementary sources to calculate $CO_2$ emissions and to determine energy consumption for 12 FG countries. We tested our hypothesis by comparing the leading goose of Japan, 2nd tier NIEs (Taiwan, Korea, Singapore, and Hong Kong), ASEAN countries (Thailand, Malaysia, Philippines, Indonesia, and Vietnam), and 3rd tier of China and India to test our hypothesis. Among the 12 countries of the FG group, Table 1 lists mean, SD, and mean-to-SD ratio of the percentage of TPES of three major brown energy sources for each country. Not every country had a relatively constant energy matrix. For example, 25% of total energy produced and imported in Korea was from coal. However, as the highest percentage of brown energy, its 95% confidence interval (CI) ranges widely from 11.28% to 38.72%, corresponding to a mean-to-SD ratio as low as 3.84. In contrast, coal accounted for 66% of energy produced and imported in China and was relatively constant across decades (95% CI = 60.12%–71.88%). Based on Table 1, we selected seven countries with mean-to-SD ratio of dominant energy greater than 7—Japan, Taiwan, Thailand, Malaysia, China, Indonesia and India—for further analysis.

We applied non-linear mixed effects modeling to plot per capita $CO_2$ emissions in Japan, Taiwan, and China for 1960–2015. Emissions in Japan increased the earliest and plateaued after 1970 (Fig. 1). Taiwan followed, with a classical S-shaped trajectory during the same period. Taiwan's per capita $CO_2$ emissions exceeded that of Japan after 2000 and gradually plateaued thereafter. Meanwhile, per capita emissions in China mirrored the other countries and increased after 2000. Historical records of per capita $CO_2$ emissions in the other countries are shown in Supplementary Fig. 1.

Fig. 2 demonstrates per capita $CO_2$ emissions from different sectors in Taiwan and China. Using our sigmoid curve, the "flying S" model of per capita emissions fits best in secondary and tertiary industrial sectors, as they are the major economic drivers in FG theory. Total $CO_2$ emissions and per capita $CO_2$ emissions from the secondary industrial sector dropped in Taiwan in 2009, corresponding to the global financial crisis. However, the crisis did not affect total emissions in China, possibly reflecting its giant domestic market.

In the primary industrial sector, however, emissions in China and Taiwan do not mirror each other, although the scales are relatively negligible compared to other sectors ($< 0.2$ ton/person in Taiwan and $< 0.15$ ton/person in China). Per capita emissions in residential consumption were higher before 1990 in China, most probably reflecting early indoor combustion for heat. In contrast, most families in Taiwan, a tropical country, do not use coal heaters. During 1990–2000, electric heaters and electrification of household appliances gradually replaced old coal combustion heaters (Lu, 1993). Afterwards, China's emission trajectory mirrored that of Taiwan as living standards elevated.

Per capita $CO_2$ emissions vs. per capita nominal GDP illuminates $CO_2$ emissions at different levels of economic development in a country. We observed similar emission vs. GDP relationships of seven countries, further validating the assumptions of our "flying S" hypothesis (Supplementary Fig. 2).

We then used the developed models based on historical data to predict future $CO_2$ emission trajectories by country. Table 2 summarizes country-specific parameters of selected countries from our analysis. In the model, Japan reached a transition year in 1966, which is 24 years earlier than Taiwan. In China, the transition year was 2018, which implies the growth rate of per capita $CO_2$ emissions will slow down thereafter. Meanwhile, our results predicted that India will accelerate its rate of per capita $CO_2$ emissions until 2032. China had the highest plateau of 17.62 tons of $CO_2$ per capita, due to its great dependence on coal consumption (66%, Table 1).

Our analysis predicts that China will emit 12.89 (95% CI = 6.68–16.93) tons of $CO_2$ per capita in 2030, corresponding to 18252.24 $MtCO_2$/year if China's population is estimated to be 1.42 billion in 2030 (Wulf, 2016). At that time, China's total emissions will be two times higher than India and 15 times higher than Japan. Historical records of per capita $CO_2$ emissions and predicted emissions of the 6 selected countries are illustrated in Fig. 3.

The model is stable and internally validated by comparing the average RSS among selected countries and time period. The average RSS is 0.3812 in the internal validation period (2006–2010), which is comparable to 0.3886 in the external period (after 2010). The predicted per capita $CO_2$ emissions in the external period are plotted in Supplementary Fig. 3.

## 4. Discussion

Macroeconomic theories predict that countries in the same FG group follow similar industrial ladders (Kojima, 2000; Rostow, 1960), suggesting that those countries will also have similar energy consumption patterns. Further, a country's energy consumption pattern is proportional to its GHG emissions if—and only if—its energy matrix is constant across time. Indeed, limited to energy source, domestic politics and policy, facility inflexibility, and/or national security, most countries we studied had a relatively constant energy matrix. Therefore, using analysis of historical data for FG countries, ex post data supports our hypothesis and indicates that data on economic growth patterns can be transformed into predictions of GHG emission patterns.

China has witnessed rapid and large-scale economic development. Concomitant with massive industrial growth, China has become the

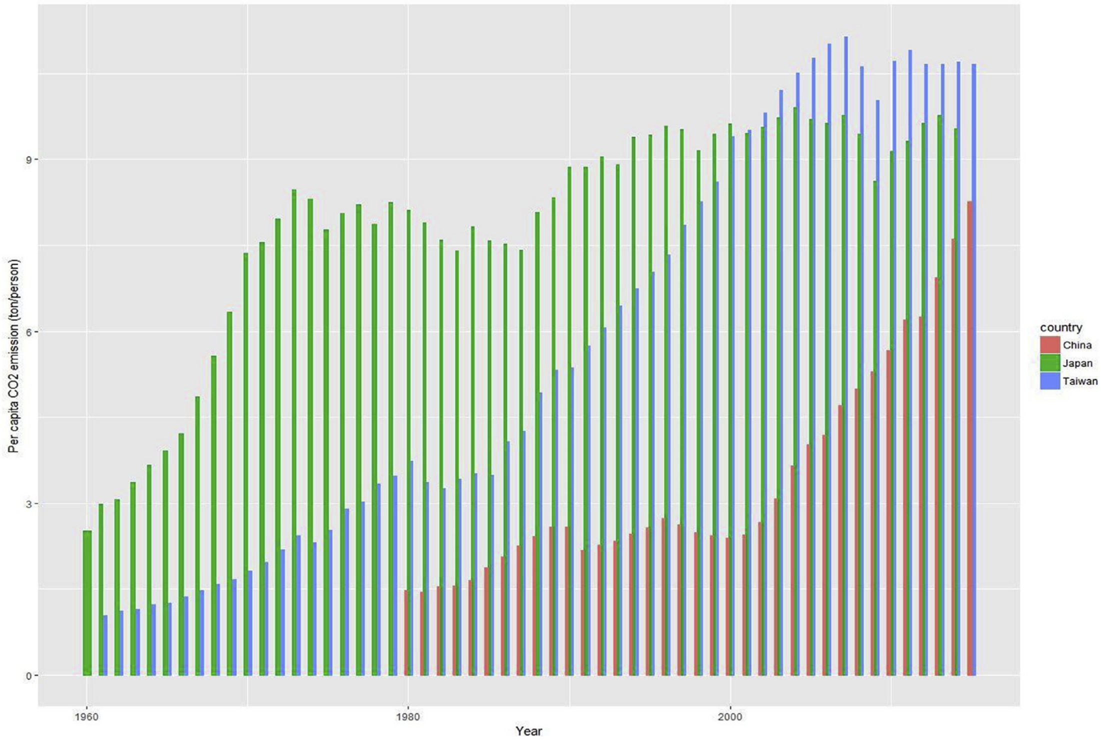


**Fig. 1. Historical $CO_2$ emissions per capita in Japan, Taiwan, and China.** A plot of per capita $CO_2$ emissions (ton/year) by year for Japan, Taiwan, and China during 1960–2015.

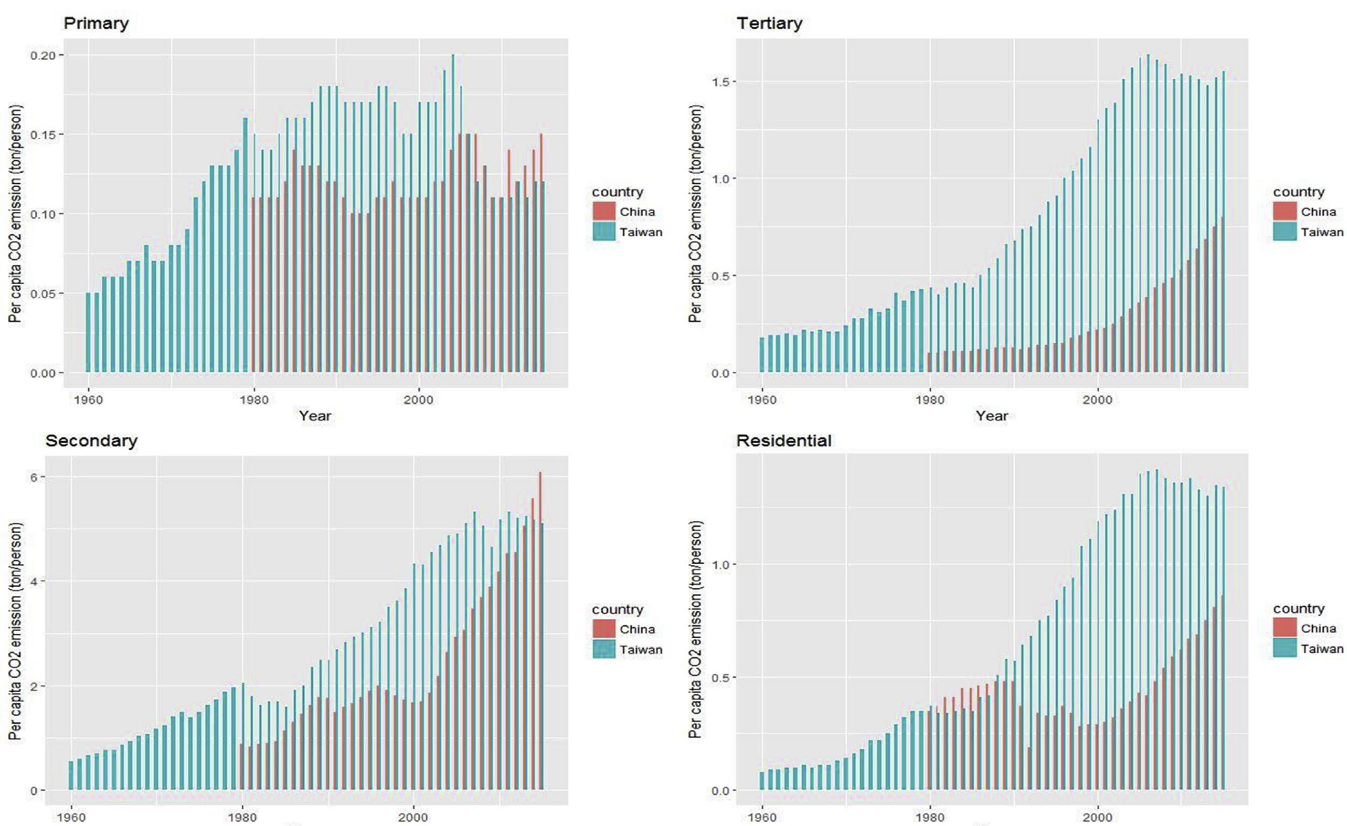


**Fig. 2. Historical per capita $CO_2$ emissions by sector in Taiwan and China.** Plots of per capita $CO_2$ emissions (ton/person) by year for primary (farming), secondary (industry), tertiary (trade and transport), and residential sectors in China and Taiwan during 1960–2015.

**Table 2**
Country-specific parameters and predicted emissions of selected East Asian countries.

| | Transition year | Plateau (tons/person) | Per capita $CO_2$ emissions in 2030 (tons/person) | Population in 2030 (million people) | Total $CO_2$ emissions in 2030 (million tons) |
|---|---|---|---|---|---|
| China | 2020 | 18.47 | 12.89 (6.68–16.93) | 1416 | 18252.24 (9458.88–23972.88) |
| India | 2035 | 13.33 | 5.42 (1.81–9.79) | 1528 | 8281.76 (2765.68–14959.12) |
| Indonesia | 2031 | 13.67 | 6.63 (2.48–10.83) | 295 | 1955.85 (731.6–3194.85) |
| Japan | 1972 | 10.41 | 10.33 (9.92–10.72) | 120 | 1239.6 (1190.4–1286.4) |
| Malaysia | 1989 | 8.19 | 7.92 (7.10–8.55) | 36 | 285.12 (255.6–307.8) |
| Taiwan | 1989 | 12.47 | 12.04 (10.83–12.78) | 24 | 288.96 (259.92–306.72) |
| Thailand | 2010 | 9.04 | 7.59 (5.06–8.80) | 68 | 516.12 (344.08–598.4) |

largest emitter of carbon dioxide ($CO_2$), contributing ~25% of total world emissions in 2014 (The World Bank data, 2015). The Chinese government has pledged to cut emissions, stating in its Intended Nationally Determined Contribution (INDC) that the country plans by 2030 to lower its $CO_2$ emissions per unit of GDP by 60%–65% of its 2005 level (INDC, 2015).

Using empirical data to confirm our theory, we extrapolate $CO_2$ emissions of selected countries in year 2030 and beyond. We predict China will emit 18252.24 $MtCO_2$/year (95% CI = 9458.88–23972.88) in 2030 and $CO_2$ emissions per unit of GDP in China will be 0.49 kg/USD in 2030, which easily meets China's INDC 2030 goal to lower $CO_2$ emissions per unit of GDP by 60%–65% of the country's 2005 level (1.82 kg/USD).

These predictions are comparable to other studies. For example, reviewing of 164 scenarios from 15 models predicted annual $CO_2$ emissions from fossil fuels and industry in China in 2030 will range from 8000 $MtCO_2$/year up to 18,000 $MtCO_2$/year in different scenarios (Chen et al., 2016; Li and Qi, 2011; Grubb et al., 2015). Altogether, our

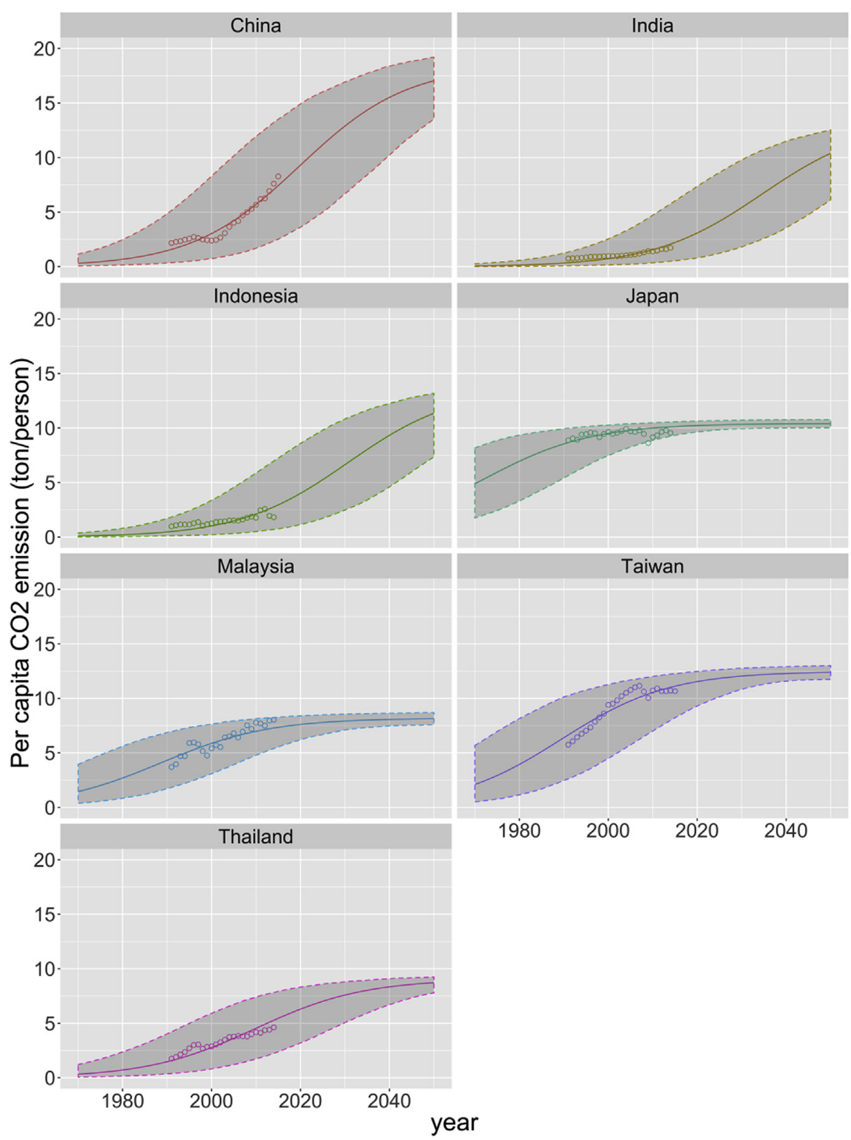


**Fig. 3. Historical and predicted per capita $CO_2$ emissions in selected countries.** Plots of per capita $CO_2$ emissions (ton/person) by year for China, India, Indonesia, Japan, Malaysia, Taiwan, and Thailand for 1960–2040.

approach provides another means to predict GHG emissions for countries within an FG group and could be an important application of FG paradigm in climate change.

### 4.1. Limitations

FG model is popular and unique in East Asian. Researches on the generalizability of the model outside East Asian countries are limited (Kojima, 2000; Rostow, 1960) due to different industrialization and economic growth patterns. Critiques of the FG model may arise in the context of the "flying S" hypothesis (Kasahara, 2013; Hart-Landsberg and Burkett, 2008; Honda, 2017). However, most are not quite relevant to $CO_2$ emissions. For example, some have suggested the inward-looking Chinese economy is very different from the economic structures in Japan and first-tier NIEs (Kasahara, 2013; Peng, 2000), indicating that the economies will have different patterns of growth. In addition, regionalization of East Asia has not been self-contained. While technology and capital may be dominantly outsourced from Japan, final products are exported to third-party markets outside the region (Kasahara, 2013). However, those concerns are mainly from a consumption, rather than production, side. Whether markets are inside or outside the region, industrial processes incur GHG emissions, not the market location.

In addition, a constant energy matrix across time might be viewed as a strong assumption. For example, U.S. energy mix has changed significantly since 2007 due to the shale gas revolution, which dramatically impacted economics, geopolitics, and national security (Maria Luisa ParraguezKobek and CamperoAguilar, 2015). However, the global energy mix has not changed significantly over the last 50 years, especially in many East Asian counties (Trade and Development Boa, 2010). Further, we carefully examined assumptions on historic data before fitting the model. In addition, however, calculations of emission data might be hazy in some countries. For example, emissions from various international organizations and the Chinese Year Book differ due to varying scopes, methods, and underlying data for fossil fuel consumption and emission factors (Zhu, 2014). To bypass those discrepancies, we used the IPCC bottom-up method with a country-specific emission factor, consistent across time. Possible overestimation of $CO_2$ emission might exist among the other countries using IPCC default values for emission factor. However, the overestimation is less likely to bias the result since (Kojima, 2000) percentage of coal are not as high as China or Taiwan (Table 1) and (Kasahara, 2013) we focus on the chronological trend and the emission factors are fixed across time.

Setting plateau by only using coal percentage might be lack of considering other types of energy, such as oil, gas or even green energy. However, we would have a problem of collinearity since the percentages of coal plus oil and gas add to 100% for some countries. Using predicted percentages of renewable energy also fails to stick to "business as usual" (BAU) scenario.

Finally, our analysis did not consider policy, industrial restructuring or advanced technology in the future, though the effect of those challenges remains unknown. Some researches predicted a higher penetration of renewable energy in the future (Roseberry, 2017); some estimated industrial structure adjustment might change $CO_2$ emission in China (Yu et al., 2018). Therefore, our predictions can be and should be interpreted as BAU, driven and limited to macroeconomic growth in the region. Indeed, most scholars still believe the scale effect of economic growth might be the dominant drive to $CO_2$ emissions, outweighing any magic bullet of technology (KaisSaidi, 2015; BirgitFriedl, 2003). For example, the total capacity of carbon capture and storage is forecast to increase to 2000 GW by 2030 and 2500 GW by 2050 (Chen Wenying et al.). However, these technologies may still not be mature enough to mitigate GHG emissions, especially on such a large scale as in China (Wu, 2017). Further, although costs of renewable energy have dropped dramatically in the recent decade, total energy replacement by renewables is still limited in the economically based world and therefore causes mismatch in consumption and production (JinYang HH et al., 2016).

## 5. Conclusions

Our study bridges a well-known FG paradigm in macroeconomics to study climate change and proposes a "flying S" hypothesis to predict GHG emissions of FG countries. The "flying S" hypothesis provides a framework to describe and understand GHG emission trajectories of developing countries under the context of East Asian development.

## Competing interests

We declare that we have no conflict of interest.

## Ethics approval

The study had been reviewed and approved by Harvard T.H. Chan School of Public Health Office of Human Research Administration (IRB protocol #: IRB16-2125).

## Declaration of interest

None.

## Consent for publication

Not applicable.

## Availability of data and material

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Competing interests

The authors declare that they have no competing interests.

## Author contributions

Cheng-Kuan Lin contributed to idea formulation, study design, data preparation, data analysis, reporting results, data interpretation, and manuscript preparation. Tom Chen and Xihao Li contributed to data analysis and data interpretation. Nathalie De Marcellis-Warin, Cory Zigler, and David C. Christiani contributed to interpretation of the data. All authors have seen and approved the final version.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.01.081.

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